Recession Aversion at the Bank of England: Insights from Monetary Policy Committee Members' votes

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Outline

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Motivation and research questions

"A former Bank of England informant said: You learn from the past. There is something else. Knowledge is made up of training and experience. For example, I often used to divide the members of the Monetary Policy Committee over whether they had been involved in some of the great policy disasters of the United Kingdom. If you had been involved in those policy disasters you had a very different take on life. (12 March 2002)". [from Pixley (2004)]

- Where do central bankers' preferences come from?
  - Are they innate, directly inherited, or acquired by some more oblique transmission channels?
- What are the consequences of acquired / formed preferences on policy?
- What is the role of the interactions inside the MPC?

Aims and contributions

- Empirics: Revealing past determinants of voting behavior of the Bank of England's MPC members
- Methodology: taking into account and interpreting spatial interdependencies in a discrete choice modeling framework

Evidence on early-life formation of preferences

- Dohmen et al. (2011): parents transfer risk-attitudes to children
- Emmeneger et al. (2017): early-life experiences “scar” people
- Malmendier & Nagel (2011): “depression babies” have lower willingness to take financial risk, and are more pessimistic about future stock returns

What happens when ‘depression babies’ grow-up as policy-makers? Are they more risk-averse? More recession-averse?

- Malmendier et al. (2017) show impact on inflation aversion for FOMC members: their speeches are more “dovish”.
- Farvaque et al. (2020) demonstrate in a panel of central banks that longer experience of recession in early life lowers the probability of interest rate hikes, ceteris paribus
- Farvaque et al. (2021) argue that central bankers who have been exposed to disasters in early life tend to manage inflation in a more conservative way
- Aslam and Farvaque (2021) show that central bankers who experienced episodes of epidemics in their early life lowered interest rates faster and lower during the COVID-19 pandemic

Evidence on leadership effects

- Initiated in Management studies – ”coporate elites” or „upper echelon” literature, e.g. Hambrick and Mason (1984) or Jensen and Zajac (2004)
- Besley et al. (2011), Hayo and Neumeier (2012), …:
  leaders’ background matters in macroeconomic developments
- Chappell et al. (2005), Eichler and Lahner (2013), …:
  true for FOMC members
- Gohlmann and Vaubel (2007), Farvaque et al. (2011, 2014), Lebaron and Dogan (2016):
  verified for central bankers in general
- If leaders matter, their experiences should matter too!

Spatial interdependence in panels and voting

- Pesaran (2004, 2006, 2015) provides a setup for testing spatial interdependence in panels in general (cross-section or common correlated effects).
- More recently, Bhattacharjee, Ditzen & Holly (2020) use the mean group, common correlated effects estimator to provide a set of weakly cross correlations that they treat as spatial weights.

In monetary policy context:

- Bhattacharjee & Holly (2009) study BoE MPC and uncover the voting structure with two dimensions – internal-external and hawk-dove.
- Bhattacharjee and Holly (2015) estimate the spatial weights matrix between the members and identified several sources of heterogeneity in the individual policy reaction functions.

Data

- Bank of England's Monetary Policy Committee:
  - Period: 1999M1 – 2018M9
  - MPC members: 39 effectively
  - Meetings: 224
  - Votes: 1990
- Bank of England: Bank rate
- IMF: Inflation and GDP forecasts
- Hand-picked: members' characteristics and experiences
- Dummies: GFC (Leaven), Brexit

Methods (1): Multinomial logit

Y_{it} = [0, 1, 2] (0 – status quo, 1 – a hike, and 2 – a cut in interest rates).

$$Prob(Y_{it} = j) = \frac{e^{\beta_j' \boldsymbol{x}_{it}}}{\sum_{k=0}^{2} e^{\beta_k' \boldsymbol{x}_{it}'}}$$

after transformation ensuring that probabilities sum-up to 1:

$$Prob\left(Y_{it} = j \middle| X_{it}\right) = \frac{e^{\beta_j' \boldsymbol{x}_{it} + \varepsilon_{it,j}}}{1 + \sum_{k=1}^{2} e^{\beta_k' \boldsymbol{x}_{it} + \varepsilon_{it,k}}}$$

Where j = 0, 1, 2 and $\beta_0 = 0$.

Methods (2): Dealing with network dependence

- Standard approach:

  1) estimate a linear model:

  $$Y_{it} = \alpha + \beta X_t + W_i + \gamma Z_{it} + \varepsilon_{it}; \;\; i = 1, \cdots, N; t = 1, \cdots, T$$

  2) construct an estimated cross-member correlation matrix from these residuals

  3) test weak dependence using the Pesaran (2015) test

  4) if weak dependence is rejected, then the residuals' structure needs to be modeled, e.g. as: $\boldsymbol{\varepsilon}_t = M\boldsymbol{\varepsilon}_t + f_t\boldsymbol{\delta} + \boldsymbol{\eta}_t$:

  - global shocks captured by factor structure $f_t\boldsymbol{\delta}$;
  - cross-member spillovers based on committee network structure, $M\boldsymbol{\varepsilon}_t$ (Bhattacharjee and Jensen-Butler, 2013; Bhattacharjee and Holly, 2013).

Methods (2): Dealing with network dependence – our approach

- Recent large panel literature highlights spatial (network) dependence as a combination of two effects
  - Factor structure, with time specific factors interacted with member (unit) specific loadings – this typically leads to spatial (network) strong dependence
  - (Stationary) spillovers between units contributing to weak dependence – typically modelled by spatial weights
- Modeling strong dependence using factor structure is crucial. Without this, model estimates reflect spurious correlation and are usually inconsistent
- Initially, before accounting for factor structure, we find evidence of strong dependence – Pesaran (2015) CD statistic 15.9 (p-value= 0). The question is: how to account for factor structure. We do this by a combination of approaches
  - Common correlated effects (Pesaran 2006) – we use median vote rather than mean because in our voting model, the median has special significance
  - Observed factors: Brexit and output gap – with heterogenous loadings – reflecting different views on the underlying structural model of the economy, or exposure to Brexit period, or uncertainty about output gap
  - Statistical factor analysis: 12 statistical factor decomposition of voting structure, including one with heterogenous loadings
  - We also tried a Lasso procedure but did not include this in the final model specification
- Weak dependence is modelled by statistically significant cross-correlations in the residuals, with usual IV/GMM method to deal with endogeneity (Bailey, Holly & Pesaran, 2016)
- Finally, **CD statistic is reduced to 1.68 (p-value= 0.09)**. We combine all the above modeling into a unified weights matrix and interpret network structure by its elements.

Empirics 1: Multinomial logit without network

	Model (1)		Model (2)		Model (3)	
VARIABLES	Hike	Cut	Hike	Cut	Hike	Cut
crisis_leaven_dummy	-2.131***	2.179***	-2.054***	2.185***	-2.003***	2.041***
	(0.733)	(0.225)	(0.733)	(0.223)	(0.731)	(0.216)
brexit	0.841***	0.509	0.944***	0.389	1.003***	0.356
	(0.314)	(0.432)	(0.311)	(0.428)	(0.313)	(0.430)
PRES_affinity_rate	-0.0435***	-0.0422***	-0.0439***	-0.0432***	-0.0439***	-0.0429***
	(0.00392)	(0.00417)	(0.00392)	(0.00419)	(0.00392)	(0.00423)
gender_dummy	-0.648**	-0.193	-0.561**	-0.360	-0.608**	-0.406*
	(0.254)	(0.237)	(0.249)	(0.234)	(0.254)	(0.241)
currentbankrate(-1)	23.03***	26.80***	22.74***	25.63***	22.82***	27.65***
	(5.491)	(6.005)	(5.536)	(5.960)	(5.513)	(5.959)
age	0.00150	-0.0230	-0.0129	-0.0189	-0.0145	0.00174
	(0.0148)	(0.0160)	(0.0140)	(0.0150)	(0.0127)	(0.0137)
gdp_var_forec_yr1_imf	0.454***	-0.179	0.434***	-0.172	0.418***	-0.182
	(0.152)	(0.168)	(0.151)	(0.167)	(0.151)	(0.168)
infl_var_forec_yr1_imf	0.786***	0.274	0.746***	0.290	0.725***	0.299
	(0.242)	(0.234)	(0.240)	(0.233)	(0.239)	(0.233)
int_ext_dummy	0.146	0.197	0.0225	0.321*	0.00247	0.362*
	(0.191)	(0.194)	(0.181)	(0.185)	(0.177)	(0.186)
OVERALLHOMOGENEITY	-6.187***	-1.450	-5.284***	-2.427	-4.852***	-2.424
	(1.676)	(1.881)	(1.626)	(1.835)	(1.644)	(1.853)
Rec_longest	-0.229**	0.342***				
	(0.105)	(0.119)				
Rec_total_1_25			-0.0152	0.245***		
			(0.0691)	(0.0792)		
Rec_total_pres_4Y					0.179	0.288
					(0.168)	(0.180)
Constant	4.156***	1.413	4.206***	1.203	3.949***	1.157
	(1.241)	(1.347)	(1.232)	(1.344)	(1.232)	(1.363)
Observations	1,990	1,990	1,990	1,990	1,990	1,990

Empirics 1: Multinomial logit with ”heuristics”

	Model 7		Model 8		Model 9	
VARIABLES	Hike	Cut	Hike	Cut	Hike	Cut
crisis_leaven_dummy	-1.498**	1.921***	-1.445*	1.889***	-1.336*	1.924***
	(0.746)	(0.283)	(0.747)	(0.282)	(0.743)	(0.280)
brexit	0.104	1.158**	0.217	1.087**	0.256	0.958*
	(0.368)	(0.536)	(0.363)	(0.532)	(0.364)	(0.536)
PRES_affinity_rate	-0.0485***	-0.0505***	-0.0484***	-0.0507***	-0.0485***	-0.0509***
	(0.00440)	(0.00501)	(0.00440)	(0.00503)	(0.00436)	(0.00510)
gender_dummy	-0.735**	-0.140	-0.595**	-0.159	-0.605**	-0.0327
	(0.294)	(0.282)	(0.287)	(0.278)	(0.291)	(0.291)
currentbankrate_PS_lag	9.170	29.64***	9.555	30.11***	8.774	28.87***
	(6.399)	(8.248)	(6.458)	(8.202)	(6.436)	(8.068)
age	0.00926	0.00653	-0.00436	0.0147	-0.0134	0.0169
	(0.0176)	(0.0217)	(0.0167)	(0.0210)	(0.0154)	(0.0181)
gdp_var_forec_yr1_imf	0.420**	-0.216	0.398**	-0.207	0.379**	-0.167
	(0.173)	(0.224)	(0.172)	(0.223)	(0.171)	(0.225)
infl_var_forec_yr1_imf	0.529**	0.127	0.493*	0.136	0.474*	0.155
	(0.263)	(0.321)	(0.260)	(0.322)	(0.256)	(0.327)
int_ext_dummy	0.504*	0.566*	0.384	0.618**	0.326	0.651**
	(0.257)	(0.308)	(0.247)	(0.299)	(0.241)	(0.301)
OVERALLHOMOGENEITY	-9.353***	1.567	-8.217***	1.259	-7.975***	0.791
	(1.946)	(2.752)	(1.864)	(2.719)	(1.890)	(2.749)
hike_ext_sen_dummy	2.234***	-14.06	2.225***	-15.32	2.208***	-15.16
	(0.309)	(737.7)	(0.308)	(1,372)	(0.304)	(1,200)
cut_ext_sen_dummy	-1.829*	2.845***	-1.945*	2.875***	-1.955*	2.979***
	(1.034)	(0.310)	(1.032)	(0.308)	(1.033)	(0.317)
hike_int_sen_dummy	3.772***	-14.85	3.723***	-16.06	3.645***	-15.71
	(0.326)	(2,025)	(0.323)	(3,836)	(0.317)	(3,396)
cut_int_sen_dummy	-15.96	4.797***	-17.20	4.825***	-17.02	4.892***
	(2,985)	(0.370)	(5,595)	(0.372)	(4,955)	(0.376)
Rec_longest	-0.337***	0.0424				
	(0.126)	(0.156)				
Rec_total_1_25			-0.116	-0.0376		
			(0.0811)	(0.108)		
Rec_total_pres_4Y					-0.0137	-0.397
					(0.195)	(0.249)
Constant	5.460***	-1.485	5.584***	-1.517	5.442***	-1.433
	(1.495)	(1.839)	(1.488)	(1.831)	(1.495)	(1.840)
Observations	1,990	1,990	1,990	1,990	1,990	1,990

Empirics 1: Multinomial logit with network str.

VARIABLES	Cut	Hike
Global Financial Crisis	0.466	-0.567
	(0.390)	(0.762)
Gender dummy	0.122	-1.160***
	(0.351)	(0.439)
Bank Rate lag	45.72***	21.48***
	(9.863)	(6.817)
GDP growth rate forecast	0.384	0.0214
	(0.678)	(0.471)
Inflation growth rate forecast	0.263	-0.494**
	(0.454)	(0.247)
Successive years of recession	0.412***	0.0223
	(0.139)	(0.142)
Median vote	-4.135***	4.649***
	(0.433)	(0.406)
Brexit McCafferty	0.462	3.655***
	(2.391)	(0.608)
Brexit Saunders	-15.90	2.076*
	(14,897)	(1.126)
GDP Allsopp, Bell, Nickell, Wadhwani	2.842***	0.754
	(1.006)	(1.170)
GDP Spencer	-0.509	2.241***
	(1.537)	(0.659)
GDP Blanchflower	-4.563**	0.582
	(2.050)	(2.561)
GDP Walton	-32.21*	17.70***
	(18.72)	(6.394)
GDP Vickers	99.33	-6.281**
	(4.968e+06)	(3.130)
GDP Weale	-0.549	2.768***
	(2.570)	(0.681)
GDP Sentance	0.266	5.904***
	(2.401)	(1.433)

VARIABLES	Cut		Hike
Inflation Alsopp, Clementi, Vlieghe, Bell, Nickell	2.926**		1.374
	(1.445)		(1.185)
Inflation Julius	7.466*		-0.666
	(4.080)		(3.033)
Inflation Vickers	285.8		-17.80**
	(1.759e+07)		(7.422)
Inflation Saunders	-5.080		6.042*
	(78,424)		(3.323)
Inflation Large	0.0879		-2.626**
	(2.118)		(1.258)
Inflation Wadhwani	14.38***		1.062
	(3.823)		(3.621)
Network matrix	-55.22***		60.58***
	(12.83)		(11.21)
Constant	-6.025***		-4.115***
	(0.536)		(0.378)
Observations	1,990	1,990	1,990

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Empirics 2: Describing network structure

- More but weaker positive influences and less but stronger negative influences
- Positive influences on average do not differ within groups (slightly stronger for external members)
- Negative influences on average are stronger among internals and weaker among external members

Table 6 : Counts of positive and negative influences by type of member

type of member	positive	negative	0	Total
Ext -> Ext	245	122	74	441
Ext -> Int	220	111	47	378
Int -> Ext	228	129	21	378
Int -> Int	170	120	34	324
Grand Total	**863**	**482**	**176**	**1521**

Table 7 : Average Influence by type of member

type of member	positive	negative	Total
Ext -> Ext	0.0177	-0.0288	0.0022
Ext -> Int	0.0174	-0.0328	0.0005
Int -> Ext	0.0145	-0.0332	-0.0028
Int -> Int	0.0144	-0.0422	-0.0090
Total	**0.0161**	**-0.0342**	**-0.0019**

Empirics 2: The most influential and influenced members

Table 8 The most influential members by absolute value

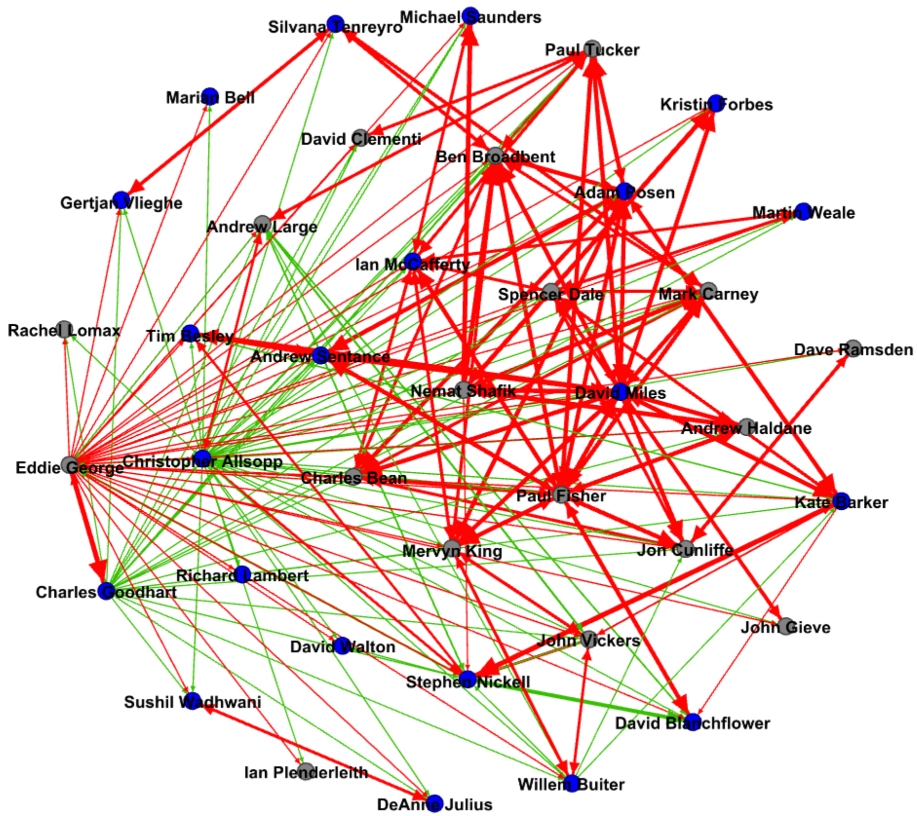
Member	Int/Ext	Total Abs. Inf.	Most influenced members
David Miles	Ext	2.009	Kate Barker, Jon Cunliffe, Charles Bean, Paul Tucker, Andrew Sentence...
Paul Fisher,	Int	1.814	Ian McCafferty, Andrew Sentence, Jon Cunliffe, Ben Broadbent, Mark Carney...
Nemat Shafik	Int	1.609	Michael Saunders, Ben Broadbent, Mark Carney, Andrew Haldane, David Miles..
Adam Posen	Ext	1.453	Kate Barker, Andrew Sentence, Ben Broadbent, Charles Bean, Mervyn King
Eddie George	Int	1.367	Charles Goodhart
Christopher Allsopp	Ext	1.276	Stephen Nickell, Andrew Large, Jon Cunliffe, Sushil Wadhwani, Willem Buiter
Jon Cunliffe	Int	1.195	Charles Bean, Spencer Dale, Dave Ramsden, Willem Buiter, Stephen Nickell
Willem Buiter	Ext	1.182	John Vickers, Mervyn King, Kate Barker, Andrew Large, Jon Cunliffe, St. Nickell
Charles Goodhart	Ext	1.165	Eddie George, Willem Buiter, Stephen Nickell
...			
Mervyn King	Int	0.924	John Vickers, Willem Buiter, Ben Broadbent, Ian McCafferty, Stephen Nickell
Mark Carney	Int	0.919	Ben Broadbent, Charles Bean, Spencer Dale

Table 9 The most influenced members by absolute value

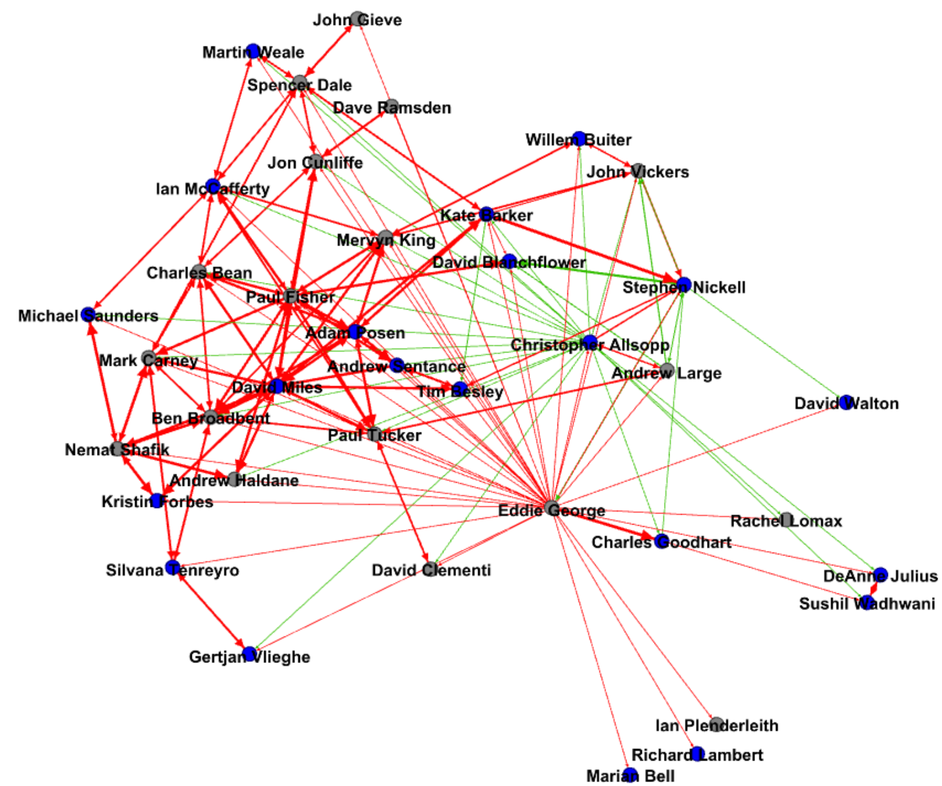
Row Labels	Int/ext	Tot. Inf. Rec	Most influenced by
David Miles	Ext	1.491	Adam Posen, Paul Fisher, Nemat Shafik, Christopher Allsopp, Charles Goodhart
Paul Fisher	Int	1.295	Adam Posen, David Miles, David Blanchflower, Charles Goodhart, Christoph Allsopp
Ben Broadbent	Int	1.236	Nemat Shafik, Adam Posen, David Miles, Paul Fisher, Charles Goodhart, Chris Allsopp
Mark Carney	Int	1.074	Silvana Tenreyro, David Miles, Paul Fisher, Nemat Shafik
Adam Posen	Ext	1.056	David Miles, Paul Fisher, Ben Broadbent, Kate Barker, Mervyn King
Paul Tucker	Int	1.043	David Miles, Adam Posen, Paul Fisher, Ben Broadbent, Christopher Allsopp
Charles Bean	Int	1.023	David Miles, Adam Posen, Paul Fisher, Ben Broadbent, Mark Carney, Chris Allsopp
Mervyn King	Int	0.990	Adam Posen, David Miles, Paul Fisher, Ben Broadbent, Charles Goodhart, Chris Allsopp
Ian McCafferty	Ext	0.985	Paul Fisher, Mervyn King, Paul Tucker, Charles Bean, Spencer Dale, Chris Allsopp
Jon Cunliffe	Int	0.916	David Miles, Paul Fisher, Dave Ramsden, Charles Bean, Spencer Dale

Empirics 2: Illustrating network structure

Fruchterman Reingold method



AtlasForce2 method



Notes: Blue nodes: external members, Grey nodes: internal members, green arrows – positive weights, red arrows – negative weights. Edges filtered at the absolute value of 0.03. Software: Gephi

Conclusions

- In this paper we study the voting behaviour of the Bank of England's MPC in a discrete choice framework taking into consideration the network of influences in the committee
- We demonstrate that the estimated network structure purges the results from strong dependence while the effect of childhood recession remains
- Some estimated coefficients become less intutive, however.
- Further steps:
  - More regressions
  - More formal analysis of the network structure and clusters

Conclusions: some earlier ideas (to dig deeper)

- At earlier stages we constructed pseudo-residuals, potentially better suited to measure network dependence in a discrete-choice setup
- Then, we were not able to purge the results from strong dependence by a number of heuristics, including:
  - A measure of affinity (common votes) with the Chairman
  - Following the vote by the ”senior” members among internal and external members

Thank you!

- Thank you very much for your attention.
- The paper is very much a work in progres...
- Any comments and suggestions are more than welcome!